Traffic State Estimation and Prediction under Heterogeneous Traffic Conditions

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Abstract— The recent economic growth in developing countries like India has resulted in an intense increase of vehicle ownership and use, as witnessed by severe traffic congestion and bottlenecks during peak hours in most of the metropolitan cities. Intelligent Transportation Systems (ITS) aim to reduce traffic congestion by adopting various strategies such as providing pre-trip and en-route traffic information thereby reducing demand, adaptive signal control for area wide optimization of traffic flow, etc. The successful deployment and the reliability of these systems largely depend on the accurate estimation of the current traffic state and quick and reliable prediction to future time steps. At a macroscopic level, this involves the prediction of fundamental traffic stream parameters which include speed, density and flow in space-time domain. The complexity of prediction is enhanced by heterogeneous traffic conditions as prevailing in India due to less lane discipline and complex interactions among different vehicle types. Also, there is no exclusive traffic flow model for heterogeneous traffic conditions which can characterize the traffic stream at a macroscopic level. Hence, the present study tries to explore the applicability of an existing macroscopic model, namely the Lighthill-Whitham-Richards (LWR) model, for short term prediction of traffic flow in a busy arterial in the city of Chennai, India, under heterogeneous traffic conditions. Both linear and exponential speed-density relations were considered and incorporated into the macroscopic model. The resulting partial differential equations are solved numerically and the results are found to be encouraging. This model can ultimately be helpful for the implementation of ATIS/ATMS applications under heterogeneous traffic environment.

Index Terms— Intelligent Transportation System, traffic state estimation, macroscopic traffic modeling, heterogeneous traffic condition

I. INTRODUCTION

The challenges faced by urban traffic in both developed and developing countries are infrastructure deficiency, congestion, accidents, and environmental and health damages due to pollution. Though all of these are important, the problem of traffic congestion is the most visible and affects a large number of motorists directly on a day-to-day basis. Urban areas in most of the developing countries are facing major challenges in traffic management and control in recent decades and India is no exception. It has witnessed a rapid growth in economy in recent years, resulting in vehicle ownership levels growing at a much faster rate. For example, the number of registered vehicles in India's six major metropolises went up by 7.75 times during 1981 to 2001, while the population increased only by 1.89 times. Thus, the growth of motor vehicles was almost four times faster than the growth of population [1]. The World Bank reported that the economic losses incurred on account of congestion and poor roads alone run as high as $6 billion a year in India [2]. Though there are various solution options like infrastructure expansion, Transportation System Management (TSM) measures and congestion pricing, technology applications like the Intelligent Transportation System (ITS) proved to be an efficient way to reduce congestion in developed countries like U.S.A. [3]. Two of the major building blocks of ITS are the Advanced Traveler Information System (ATIS) and the Advanced Traffic Management System (ATMS). The ATIS offers users real-time traveler information enabling them to make better and more informed travel decisions that will lead to more efficient distribution of travelers to routes and modes. The ATMS detects traffic situations, transmits them to control center via a communication network, and then develops optimal traffic control strategies by combining the available traffic information. Both ATIS and ATMS require the accurate estimates of the current traffic state and prediction of its short term evolution in future in order to ensure smooth traffic flow. The techniques for traffic state estimation and prediction can be grouped into data driven approaches and model based approaches. One of the major drawbacks of data-driven methods is that they correlate the mean (observed) traffic conditions to current and past traffic data, without explicitly incorporating the physical aspects of the traffic as model based approaches do [4]. However only very few studies were reported which utilizes the macroscopic traffic flow models for online traffic state prediction and notably all of the studies were deployed under homogeneous lane discipline traffic conditions as discussed under the literature review section. There were no similar reported studies where the macroscopic traffic flow model is used for online traffic state estimation and prediction under heterogeneous traffic conditions as existing in India. Hence, the objective of the present study is to investigate the use of the existing Lighthill-Whitham-Richards (LWR) macroscopic model for traffic state estimation and prediction in a busy arterial road of Chennai under heterogeneous traffic conditions.

II. LITERATURE REVIEW

The models for traffic flow can generally be grouped as microscopic (e.g., car following model) and macroscopic models. The microscopic traffic flow models simulate single vehicle-driver units and analyze microscopic properties like the position and velocity of each individual vehicle. In contrast, macroscopic models consider the traffic stream from a macroscopic perspective and can be grouped as continuum and non-continuum models. The most popular continuum models are the hydrodynamic models, and the LWR model [5, 6] is a classical example for this. Examples for non-continuum models are models which are based on Chaos theory, Cell transmission theory, models based on dynamical systems approach, etc. The studies on model based approach of traffic state estimation and prediction basically utilizes the above said traffic flow models from a macroscopic perspective in order to estimate and predict the traffic stream parameters (flow, speed and density) and from which the other parameters like travel time can be inferred. Some of the important literature in this direction is briefly reviewed below. Nanthawichit *et al.* [7] proposed a method, where the probe data were integrated into the observation equation of the Kalman filter (KFT). They adopted a higher order macroscopic traffic flow model. Wang *et al.* [8] adopted extended Kalman filter incorporated into a higher order macroscopic traffic flow model. Daniel *et al.* [9] used the inverse modeling technique based on the LWR model that used velocity measurements from Global Positioning System (GPS) enabled mobile devices for highway traffic state estimation. Herrera *et al.* [10] proposed two methods, one based on Newtonian relaxation and other based on Kalman filtering technique to integrate Lagrangian measurements into a traffic flow model to perform traffic state estimation. The literature reviewed so far corroborated their results (either by simulation or field data) in a homogeneous lane-disciplined test bed and moreover the macroscopic models like LWR, Payne, etc., were developed for homogeneous traffic conditions. In developing countries like India, the traffic conditions are highly heterogeneous in nature, where the composition of traffic comprises both motorized and non-motorized vehicles with diverse static and dynamic vehicular characteristics using the same right-of-way. The vehicles move by sharing the available lateral as well as the linear gaps. Also, the unique driver behavior and lane-less movement further add to the complexity of analyzing/ modelling mixed traffic. However, only limited studies reported the use of macroscopic models for characterizing heterogeneous traffic conditions, and are reviewed below. Logghe *et al.* [11] developed an extended LWR model for heterogeneous traffic flow by considering a separate fundamental relation for each class of vehicles. Tang *et al.* [12] proposed a new dynamic car-following model by applying the relationship between the microscopic and macroscopic variables. Padiath *et al.* [13] proposed the use of dynamical systems approach for modelling heterogeneous traffic conditions. The above literature show that most of the models developed for heterogeneous traffic conditions are microscopic in nature and results were corroborated by simulation. The online/real time optimal traffic control as employed in most ATMS applications requires the traffic flow model represented in a macroscopic way rather than microscopic, since macroscopic traffic models only work with aggregate variables and do not describe the traffic situation on the level of independent vehicles and they are less computationally intensive than microscopic models. However, there were no reported studies which can use a macroscopic model like LWR for real time traffic state estimation and prediction under heterogeneous traffic conditions. The present study is one of the first attempts in this direction which tries to explore the use of the existing macroscopic model for estimation and short term prediction of traffic flow under heterogeneous traffic conditions.

III. DATA COLLECTION AND EXTRACTION

The study corridor selected for the present study is one of the busy arterial roads in Chennai, named as Rajiv Gandhi Salai. It is a six lane roadway and about 30,000 vehicles use this road daily. The purpose of any traffic flow model is to predict the evolution of traffic into the future from some initial conditions and time varying data. In order to have the initial conditions and time varying data, it was decided to videotape the traffic conditions at two end points (named as "entry" and "exit" hereafter) located within the first 2 km section of the study corridor. The videotaping was carried out for one hour for about 5 days during the afternoon peak hour. In order to check the compatibility of the model in platoon and normal flow conditions as well as no ramp and with ramp conditions, the first day's data represents a 1 km section with platoon flow and no ramp, whereas the other days represent a 750 m section with normal flow and one ramp in between. Extraction of video involved manual counting of each one minute flow with the following classification adopted – two wheeler, Auto, Light Motor Vehicle (LMV) and Heavy Motor Vehicle (HMV). Since the macroscopic traffic flow model considers only passenger cars, it was decided to apply Passenger Car Unit (PCU) conversion as per Indian Road Congress (IRC) guidelines [14]. The time rate of change in the number of cars at entry and exit is the input for the estimation scheme, which is described in the next section.

IV. ESTIMATION SCHEME

The estimation scheme put forth here is a model based approach of traffic state estimation and prediction and is motivated from Ang *et al.* [15]. The scheme uses the well known LWR macroscopic traffic flow model. The LWR model involves a partial differential equation (PDE) in space and time, and can be solved by either analytical or numerical methods. With current high performance computing facilities, the numerical solution of this equation has been carried out. In this section, the basic equations of the LWR model are first explained. Next the finite difference formulation for solving the PDE is explained. Finally, the treatment of initial and boundary conditions is explained.

A. *Basic Equations of the LWR Model*

The LWR is a simple continuum model for traffic flow,

where an analogy is made between the vehicular flow and the flow of a compressible fluid. The two basic aspects of this model are (a) traffic flow is conserved, that is, the total number of vehicles is conserved; and (b) there is a relationship between speed and density, or between flow and density. The conservation equation is given by

$$\frac{\partial k}{\partial t} + \frac{\partial q}{\partial x} = 0. \quad (1)$$

where k and q represent the traffic density and flow rate respectively and the independent variables x and t represent space and time respectively.

The LWR model is usually accompanied by the fundamental relationship given by

$$q = uk. \quad (2)$$

where u is the mean speed of vehicles travelling along the stretch of road under consideration.

To complete the model, a speed-density relationship (i.e., an equation linking the mean speed u and density k) is needed. One of the simplest relationships relating speed and density is the Greenshield's linear model [16] given by

$$u = F\left(1 - \frac{k}{K}\right). \quad (3)$$

where F is the free flow speed and K is the jam density. Equations (1) - (3) form a set of basic equations describing the LWR model.

B. Finite Difference Formulation

Equations (1)-(3) may be solved numerically using a finite difference formulation of the time and space derivatives. To do so, the solution domain in the x-t space is first discretized using a rectangular grid with grid spacing given by "x and "t in the x and t directions respectively. For ease of implementation, the grid spacings are chosen to be uniform throughout. The discrete space and time domain indices are denoted by j and n respectively, so that at any intersection point in the grid, the density and flow are denoted by k_j^n and q_j^n respectively. The finite difference formulation used in the present study involves a 'forward–time backward–space', or FTBS scheme. In this scheme, the time derivative is approximated using the current grid point and the corresponding grid point in the next time level, while the space derivative is approximated using the current grid point and the corresponding grid point in the previous space step. Thus with the space-time domain, (1)-(3) may be rewritten as

$$\frac{q_j^n - q_{j-1}^n}{\Delta x} + \frac{k_j^{n+1} - k_j^n}{\Delta t} = 0. \quad (4)$$

$$q_j^n = u_j^n \, k_j^n \quad (5)$$

$$u_j^n = F\left(1 - \frac{k_j^n}{K}\right). \quad (6)$$

Rearranging the above three equations, we obtain

$$k_j^{n+1} = k_j^n\left[1 - \frac{\Delta t}{\Delta x} F\left(1 - \frac{k_j^n}{K}\right)\right] + k_{j-1}^n\left[\frac{\Delta t}{\Delta x}F\left(1 - \frac{k_{j-1}^n}{K}\right)\right]. \quad (7)$$

Thus, using (7), the density for the next instant of time can be predicted based on the previous instant data. Once this prediction is carried out for the entire discretized section, the flow at the exit point can be predicted at the required time interval by a simple conversion from density to flow using (10) discussed in section C. It is to be noted here that, the condition of $(\Delta x/\Delta t > F)$ must be satisfied in order to ensure the stability condition, i.e., a vehicle traveling at the free flow speed cannot traverse more than one cell in one time step. Equation (7) is based on the assumption of a linear speed-density relation. However, it may not be always true to assume a linear speed-density relation for urban arterials which is highly heterogeneous in nature as existing in India. Hence, it was decided to use a traffic stream model, specifically developed for the present study corridor by Ajitha *et al.* [17]. As per the model, the speed-density relation takes an exponential form analogous to the Underwood's exponential speed-density relationship and is given as

$$u_j^n = 67 \, e^{-0.0038 \, k_j^n}. \quad (8)$$

The speed-density relation based on (8) indicates a free flow speed of 67 km/h, and a density at maximum flow (optimum density) as 265 veh/km.

Now rearranging (4), (5) and (8), we obtain

$$k_j^{n+1} = k_j^n\left[1 - \frac{\Delta t}{\Delta x}(67)\left(e^{-0.0038 k_j^n}\right)\right] + k_{j-1}^n\left[\frac{\Delta t}{\Delta x}(67)\left(e^{-0.0038 k_{j-1}^n}\right)\right]. \quad (9)$$

Equations (7) and (9) are the final equations used for prediction in the estimation scheme, one based on the linear speed-density relation and other on the exponential speed-density relation. The results of the prediction based on the linear speed-density relation were compared with that of the exponential speed-density relation.

C. Initial and Boundary Conditions

The first one minute flow value at entry and exit can be best utilized to frame the initial condition. For this, the flow values need to be converted to density. Using a simple rearrangement of (5) and (6), the following equation can be obtained, which can be used to compute density from flow. The same equation by simple rearrangement can also be used to solve for flow, once density is known. This equation is given by

$$k_j^n = \frac{K}{2} - \sqrt{\frac{K^2}{4} - \frac{K}{F}q_j^n}. \quad (10)$$

Once the density at entry and exit is known, a simple linear interpolation will give the density at various discretized grid points. Thus, a complete set of initial conditions will be available for use along with (7). Since the LWR model involves a first order differential equation, the boundary condition at

one end may be sufficient to solve the numerical scheme. The present study uses the boundary condition specified at entry, so that the predicted flow at exit can be compared with the actual or observed flow from the video at the exit point. The flow available at entry at every one minute time interval may be linearly interpolated for every time interval of, Δt to provide the required boundary condition. Using (10), the flow values can be transformed to density for use with (7). It is to be noted here that, only for the linear speed-density relation, the use of (10) is applicable to obtain the initial and boundary conditions. For the case of exponential speed-density relation, the flow-density relation proposed by Ajitha *et al.* [17] is directly used in place of (10) and is given as

$$q_j^n = -0.1103\left(k_j^{n2}\right) + 60.195\,k_j^n. \qquad (11)$$

V. CORROBORATION OF THE ESTIMATION SCHEME

The efficacy of the scheme proposed in the previous section was tested using the field data and the results are presented below. The free flow speed, F and jam density, K are chosen as 80 kmph and 500 cars/km respectively. The values of Δx and Δt are chosen as 50m and 2 sec in order to satisfy the stability condition as explained in section B of the estimation scheme. The estimation and prediction of density is carried out for all discretized sections at each time step , using (7) for the linear speed-density relation and using (9) for the exponential speed-density relation with the free flow speed of 67 kmph. In order to check the estimation accuracy, the predicted flow at exit is compared with the actual or observed flow from the video. A sample result is shown in Fig.1.
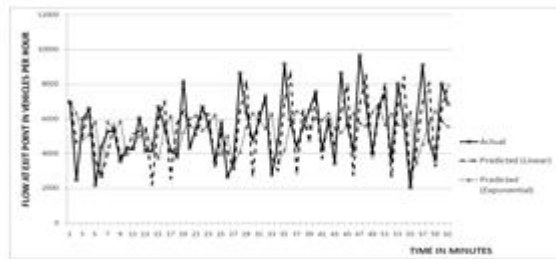

Figure 1. Predicted and actual flow at exit.

The Mean Absolute Percentage Error (MAPE) is used as a measure of estimation accuracy and is calculated using

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{q_p - q_m}{q_m}\right| \times 100.$$

where, q_p is the predicted flow at the exit, q_m is the actual flow observed from the video, n is the total number of one minute time intervals during the observation period. The MAPE values for all the five days were found and shown in Table I.

TABLE I
RESULTS OF THE MAPE

Day ID	MAPE based on linear speed-density relation (%)	MAPE based on exponential speed-density relation (%)
1	23.89	37.85
2	29.11	29.78
3	36.17	36.15
4	14.47	15.84
5	13.31	12.99

It can be seen from Table I that, on day 1, which represent a platoon flow traffic condition, the use of linear speed-density relation performs superior to that of exponential speed-density relation with a lower MAPE of 23.89. On the other days, with the normal traffic, the linear speed-density relation and exponential speed-density relation yields similar MAPE values and thus it can be concluded that, linear relation can be used for the prediction of traffic state for the study corridor considered. Also, during day 3, unlike other days, flow rate of more than 10,000 PCU's per hour was observed during selected time intervals, which may be the reason for the significantly higher MAPE in both linear and exponential model. Because in the linear speed-density relation, the free flow speed, F and jam density, K are chosen as 80 kmph and 500 cars/km which limits the capacity to only 10000 PCU's per hour. Hence, it is suggested that, there should be a balance of choosing the correct values for F and K, so that the observed flow rate in each one minute interval falls below the capacity, at the same time, it should satisfy the stability condition.

VI. CONCLUDING REMARKS

ITS has shown potential in superior traffic management in many developed countries with the aim of congestion reduction in urban areas. ITS attempts to improve the efficiency of the transportation system by using real-time and historical information on the system's status to optimally allocate resources across the transportation system components. This real-time information on the system's status requires an accurate estimation and prediction of the traffic state. The present study aims to develop a model based approach for the estimation and short term prediction of traffic flow using the LWR model using the finite difference formulation. The challenge of the present approach is to give a reliable prediction under heterogeneous traffic conditions. Both linear and exponential speed-density relations were tried out. The results obtained from the estimation scheme agree reasonably well with the measured data and use of any of the linear speed-density or exponential speed-density can be considered for prediction of traffic state for the study corridor considered. The next stage of the study will explore the possibilities of predicting other traffic parameters like travel time, and incorporating Lagrangian data obtained through GPS.

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